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The impact of public research expenditure on agricultural productivity: evidence from developed European countries

Alessandro Magrini

1. Introduction

Agricultural economists agree on the essential role of productivity growth to meet food demand of the rapidly increasing world population, and acknowledge the potentiality of public expenditure in agricultural research to stimulate the required productivity progress (Alston & Pardey, 2014). United States of America (USA) and developed European countries have been leaders in science-based agricultural productivity increase since the middle of the 20th century, motivating hundreds of quantitative studies aimed at assessing the impact of public research expenditure on agricultural productivity and the corresponding economic return. However, the almost totality of these studies has focused on USA (see Fuglie *et al.*, 2017; Baldos *et al.*, 2018; Andersen, 2019 for a review), with few scattered contributes on European countries (Thirtle *et al.*, 2008; Ratinger & Kristkova, 2015; Guesmi & Gil, 2017; Lemarié *et al.*, 2020).

This paper contributes to the literature by providing, for the first time, evidence on the economic return of agricultural research expenditure in developed European countries, making possible a comparison with existing studies focused on USA. We employ yearly data sourced from the United States Department of Agriculture (USDA), the Organisation for Economic Cooperation and Development (OECD), and the Food and Agriculture Organization (FAO) in the period 1970–2016. We follow the consolidated methodology based on a distributed-lag model relating a Total Factor Productivity (TFP) index to public research expenditure, with fixed effects to take into account the panel structure of the data. A Gamma lag distribution is assumed for the impact of research expenditure on productivity as in recent studies, due to its higher flexibility compared to trapezoidal and second order polynomial lag distributions (see Andersen, 2019, Section 4).

This paper is structured as follows. In Section 2, the data are described and the methodology is detailed. In Section 3, the results are reported and discussed. Section 4 contains concluding remarks and purposes for future work.

2. Data and methodology

Our analysis focused on the following countries: Austria (AT), Belgium & Luxembourg (BL), Denmark (DK), Finland (FI), France (FR), Germany (DE), Greece (EL), Iceland (IS), Ireland (IE), Italy (IT), Netherlands (NL), Norway (NO), Portugal (PT), Spain (ES), Sweden (SE), Switzerland (CH) and United Kingdom (UK). We considered yearly data in the period 1970–2016, specifically agricultural TFP indices computed by USDA, and Government Budget Appropriations or Outlays for R&D (GBAORD) in agriculture made available by OECD.

USDA agricultural TFP indices are available at `https://www.ers.usda.gov` under the section *Data Products – International Agricultural Productivity*. They were computed at country-level with base year 2005 using FAO and International Labour Organization (ILO) data (see Fuglie, 2018 for details).

GBAORD data from OECD are available at `https://doi.org/10.1787/data-00194-en` and represent government budget allocations for research and development by NABS 2007

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socio-economic objectives, expressed in million US dollars at 2015 prices and purchasing power parities. We selected the objective 'Agriculture' and employed these data as a proxy of public agricultural research expenditure, which is unavailable for European countries.

Data summaries by year are shown in Table 1, while Figure 1 displays quartiles and mean by year for data in level and in log return (first order difference of logarithmic values). We see that, from 1970 to 2016, the average agricultural TFP and GBAORD have increased, respectively, by 78.3% and 52.1%, with an average annual growth respectively equal to 1.3% and 0.9%.

Table 1: Data summaries by year.

Agricultural TFP (2005=100)						
Year	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
1970	43.0	55.0	62.0	66.8	75.0	112.0
1985	61.0	71.0	78.0	79.1	85.0	120.0
2000	89.0	91.0	93.0	96.9	103.0	114.0
2016	104.0	107.0	114.0	119.1	124.0	160.0
GBAORD for agriculture (million 2015 US dollars)						
Year	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
1970	15.0	46.2	62.1	137.6	215.3	468.1
1985	9.7	53.2	94.4	183.2	165.8	681.5
2000	18.6	61.1	237.8	185.3	274.9	567.7
2016	17.7	47.7	89.2	210.2	331.2	930.6

According to the economic theory, an increase in research expenditure involves an adoption lag, during which the effect on productivity rises from zero to a maximum, followed by a disadoption lag, during which the effect on productivity diminishes to zero. Thus, an appropriate model should weight the impact of research expenditure on productivity according to an inverted U-shaped function of the time lag. According to Fuglie *et al.* (2017), the most employed specifications for the weights of research expenditure include trapezoidal, second order polynomial and Gamma lag distributions, with this last one being increasingly popular in the last decade (see Andersen, 2019, Figure 1 for a graphical illustration).

We preliminarily checked weak stationarity of the country-level time series of agricultural TFP and GBAORD. The augmented Dickey-Fuller test (Dickey & Fuller, 1981) was unable to reject the hypothesis of unit root for all of them. Instead, the hypothesis of unit root was rejected for all the country-level time series taken in log return. In order to avoid spurious regression due to non-stationarity (Granger & Newbold, 1974), we worked on the time series in log return.

Let $j = 1, \ldots, J$ indicate the country and $t = 1971, \ldots, 2016$ denote the year. We specified the following model:

$$\begin{aligned} \Delta \log \mathrm{TFP}_{j,t} &= \alpha_j + \theta\, \mathrm{KS}_{j,t} + \varepsilon_{j,t} \\ \mathrm{KS}_{jt} &= \sum_{k=0}^{\infty} w_k(\delta, \lambda) \cdot \Delta \log \mathrm{GBAORD}_{j,t-k} \end{aligned} \tag{1}$$

where the variable KS is interpreted as the knowledge stock deriving from past research expenditure, and $w_k(\delta, \lambda)$ are weights of a Gamma lag distribution:

$$w_k(\delta, \lambda) = \frac{(k+1)^{\frac{\delta}{1-\delta}} \lambda^k}{\sum_{l=0}^{\infty} (l+1)^{\frac{\delta}{1-\delta}} \lambda^l} \tag{2}$$

and $\varepsilon_{j,t}$ is an exogenous random error, i.e., $\mathrm{E}(\varepsilon_{j,t}) = \mathrm{Cov}(\varepsilon_{j,t}, \mathrm{KS}_{j,t}) = 0$.

Several dummy variables were added to Model (1) in order to explain eventual structural breaks in the TFP series due to weather disasters and economic recessions: one dummy in 1974

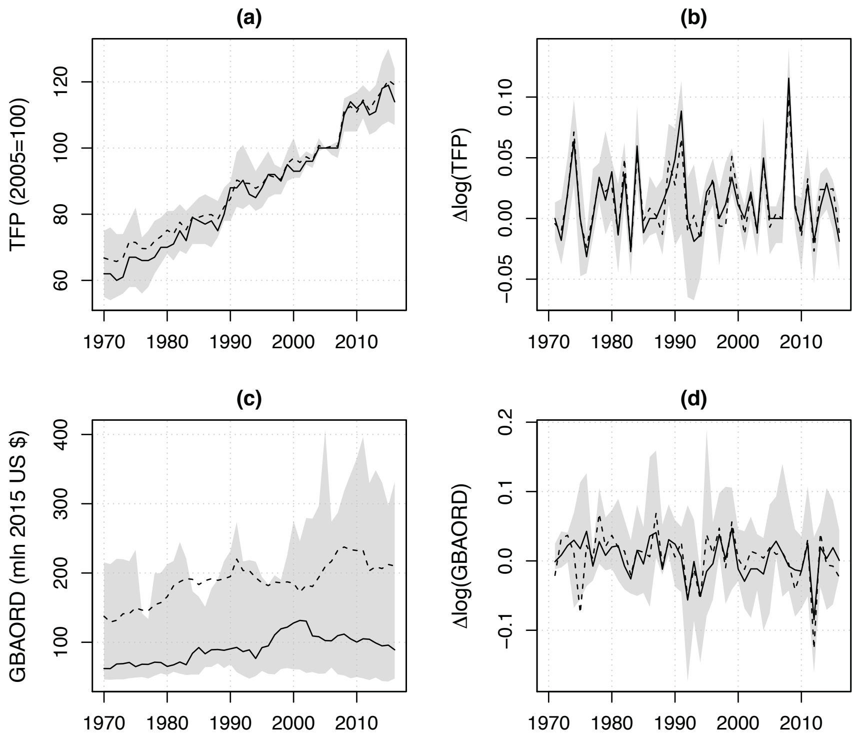

Figure 1: Time series by year. a) TFP, index 2005=100; b) TFP, log return; c) GBAORD, million 2015 US dollars; d) GBAORD, log return. Straight lines, dotted lines and shaded regions indicate, respectively, median, mean and interquartile range across the countries.

representing the European oil crisis during the 1973 Arab-Israeli war; one dummy in 2003 representing the heavy drought and heat wave which hit most European countries in that year; two dummies, one in 2008 and another one in 2012, representing the two major peaks of the European sovereign debt crisis, which was a consequence of the Great Recession in USA.

Since both TFP and GBAORD are in log return, the coefficient $\beta_k = \theta w_k$ is interpreted as the elasticity of TFP with respect to GBAORD at time lag k. Also, since the weights w_k sum to 1, parameter θ is interpreted as the long-term elasticity of TFP with respect to GBAORD.

In order to obtain maximum likelihood estimates for Model (1), we applied ordinary least squares to the models implied by several different pairs of values for δ and λ, and selected the estimates associated to the lowest residual sum of squares (see Schmidt, 1974 for details).

3. Results

We obtained the following estimates: $\hat{\delta} = 0.9$, $\hat{\lambda} = 0.6$, $\hat{\theta} = 0.172$. The standard error of $\hat{\theta}$ computed using the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator (Newey & West, 1987) resulted equal to 0.084 (p-value: 0.040). These estimates imply the lag distribution for the impact of GBAORD on TFP shown in Figure 2, which has 99th percentile at 35 years, peak at 17 years and long-term elasticity equal to 0.172 (95% confidence interval: $[0.07, 0.337]$). All the dummy variables showed a statistically significant coefficient, with an implied structural break of positive sign for the ones in 1974 and in 2008 (estimated coefficients

0.061 and 0.088, respectively) and of negative sign for the ones in 2003 and in 2012 (estimated coefficients −0.024 and −0.038, respectively).

Our resulting lag distribution for the impact of public research expenditure on productivity is a bit shorter than the ones reported by recent studies on USA. For example, Baldos *et al.* (2018) found a lag distribution with 99th percentile at 51 years, peak at 24 years and long-term elasticity equal to 0.15. Since the latest studies on USA consider a period starting from the 1950s and ending no later than 2011, while our period of analysis is from 1970 to 2016, this difference may be explained by a reduction of the adoption lag in the last one or two decades.

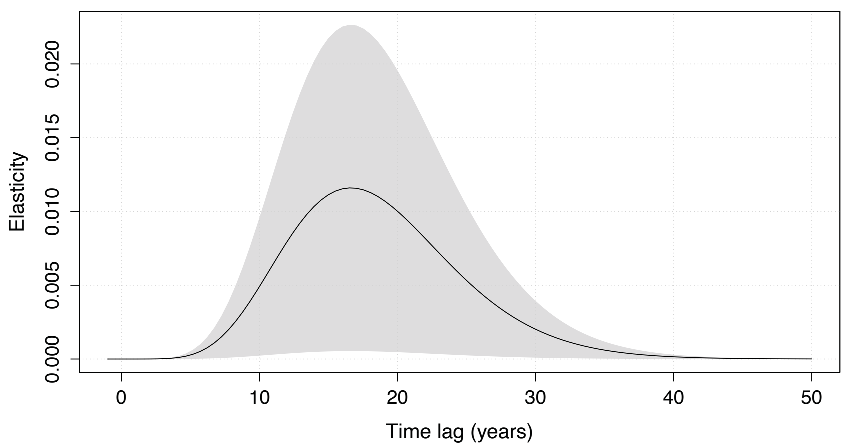

Figure 2: Estimated lag distribution for the impact of GBAORD on TFP. The shaded region represents 95% confidence bands.

Our results are only partially comparable with the ones from studies focused on specific European countries due to several reasons: a much shorter lag length is assumed (Ratinger & Kristkova, 2015; Guesmi & Gil, 2017); the lag distribution is imposed rather than estimated (Lemarié *et al.*, 2020); the considered period is outdated (Thirtle *et al.*, 2008).

After estimating Model (1), we computed the implied internal rates of return by country and compared them with the average annual change of GBAORD in recent years. To compute the internal rates of return, we employed FAO data on the real value of agricultural production in 1970–2016, available at `http://www.fao.org/faostat/en/#data` under the section *Production – Value of Agricultural Production*. Results are reported in Table 2 and displayed in Figure 3. According to our results, the countries with the highest rate of return are Germany, Spain, France and Italy (24.5–25.2%), followed by Netherlands, United Kingdom, Denmark, Greece and Belgium & Luxembourg (20.5–21.8%). However, only Germany, Denmark and Greece increased GBAORD in recent years. Norway has rate of return below the first quartile (15.8%), but it is also the country with the highest average annual change of GBAORD. Iceland, with a rate of return of 9.1%, is a negative outlier.

The estimated internal rates of return are in line with the ones reported by existing studies on USA, and they suggest that developed European countries, just like USA, could benefit from research expenditure in agriculture to a much greater extent than they currently do.

Table 2: Estimated internal rates of return and average annual change of GBAORD in different periods before 2016.

Country	Internal rate of return	Average annual % change of GBAORD 2001–2016	2006–2016	2011–2016
AT	18.8	−2.4	−1.8	−6.6
BL	20.5	−2.3	+2.5	−1.5
CH	16.3	−0.1	+0.8	+0.3
DE	25.2	+4.7	+6.0	+0.4
DK	21.2	−3.1	−1.4	+2.6
EL	20.7	−0.9	−2.8	+2.0
ES	25.2	+5.5	−4.4	−6.3
FI	17.4	−1.4	−4.3	−6.4
FR	25.1	−0.5	+3.6	−1.8
IE	18.8	+1.5	+1.6	−1.5
IS	9.1	−0.6	−1.2	−6.2
IT	24.5	+2.0	−4.2	−3.5
NL	21.8	−2.9	−7.6	−9.2
NO	15.8	+3.7	+3.4	+6.3
PT	17.1	−10.5	−10.8	−7.8
SE	18.2	−1.3	−2.9	−0.5
UK	21.4	+0.2	+0.9	−0.7

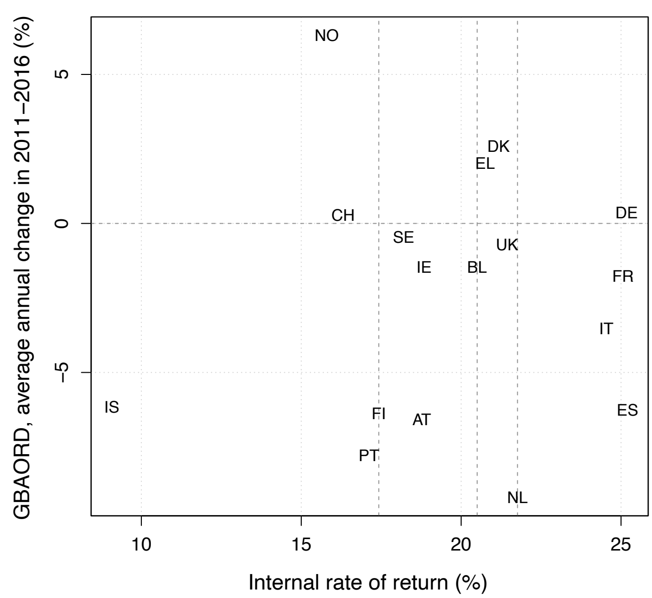

Figure 3: Internal rate of return versus average annual change of GBAORD in 2011–2016. The dotted vertical lines indicate first quartile, median and third quartile of the internal rate of return.

4. Concluding remarks

We estimated for the first time the economic return of agricultural research expenditure in developed European countries, and a comparison was made with existing studies on USA.

The main limitation of our research relies on availability and quality of data. Official statistics on actual public research expenditure in agriculture are unavailable for European countries, being available only those on government budget allocations, which have the restriction to begin in 1970, instead of in 1961 likewise USDA agricultural TFP indices. The use of budget allocations as a proxy of expenditure combined with the limited length of the time series could have significantly affected the efficiency of our estimates, as suggested by the wide confidence bands in Figure 2. Research expenditure from other countries (spillovers) and from the private sector are also expected to influence agricultural productivity, and their omission may bias the estimation of the impact of (domestic) public research expenditure. Unfortunately, data for European countries on these two further determinants of productivity are unavailable, thus they have been ignored in our analysis. In the future, we plan to estimate this missing information indirectly from available statistics. For example, spillovers could be imputed based on similarities in the budget shares for research activities across the countries (see Andersen, 2019, formula 4).

Our results highlight different rates of return across developed European countries, with Iceland being a negative outlier, suggesting the existence of unexplained heterogeneity in the relationship between research expenditure and productivity. Future work will be directed towards the identification of groups of countries with homogeneous characteristics, which could guide the specification of an opportune number of separate models.

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